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Why and Where Uncertainties

This book shows our work in the *School of Nancy* on taking into account several types of uncertainty in the assessment of dependability parameters. For this purpose, we are modeling uncertainties through additive and nonadditive theories for modeling epistemic and aleatory uncertainties. Several theories are used for this purpose in this book.

An important problem in reliability theory is to identify components within the system that significantly influence system behavior with respect to reliability or availability. Because all components cannot be improved at once to improve the system reliability, priority should be given to components that are more important. The importance measures have been developed to analyze the impact and influence of some parameters, components or group of components on the global performance of a system. The components concerned are those acting effectively to improve the system performances, or those on which to release or to impose requirements to meet or to maintain an expected level of performance. The assessment of these measures is associated with the probabilities of the system functioning (or malfunctioning) according to the state of the components. In dependability analysis, they can be used to identify the critical components, mincuts, etc., or more generally influence measures on the reliability, the availability or the maintainability of the system.

1.1. Sources and forms of uncertainty

Usually, knowledge can be defined by several characteristics such as its type and its source [DUB 10]. Based on this classification, knowledge can be generic, singular or coming from beliefs (Table 1.1). In addition, it comes from either historical-based or observation-based sources (Table 1.2).

Generic knowledge	Repeated observations as dependence rules between variables or influence links
Singular evidence	Singular situations like inspection results, test results or measurements
Beliefs	Unobserved singular events as extreme phenomenon or unrealized actions

Table 1.1. *Types of knowledge according to [DUB 10]*

Historical	Classes of situations (physical laws, statistical knowledge, etc.)
Observations	Particular situations known as true (measurements, results of tests, etc.)

Table 1.2. *Knowledge sources according to [DUB 10]*

Moreover, knowledge can be classified from other characteristics as their nature or the expression mode (Table 1.3).

Nature	Knowledge can be expressed subjectively (individual and subject to change according to people) or objectively (no personal factor in the judgment provided)
Expression	Knowledge can be qualitative (order, preference, etc.) or quantitative (scalar values, intervals with or without information, probability distribution, etc.)

Table 1.3. *Other characteristics of knowledge*

Whereas generic knowledge and singular evidences are based on observed (or observable) events, beliefs are based on unmeasured (or unmeasurable) events. Therefore, beliefs are potentially more difficult to express and can be considered more complex in terms of uncertainty. Moreover, the subjective or objective nature of knowledge implies the modes and shape of different expressions according to their dependence on the personality and the level of knowledge possessed by people or experts.

Finally, the qualitative or quantitative character of knowledge can give several kinds of expressions which are more or less precise (order, preferences, scalar values, intervals, etc.). In conclusion, the different characteristics of knowledge induce several levels of (im)precision in their expression. These levels induce uncertainties on knowledge which are mainly characterized by their sources and types.

1.2. Types of uncertainty

Many works concern the classification of uncertainties [HOF 94, FER 96, HEL 97, RIE 12]. Generally, the taxonomy of uncertainty is done with two distinct categories: aleatory or epistemic.

– Aleatory uncertainty is due to the random character or the natural variability of physical phenomena (the values are precise but different according to natural variations). Some researchers talk of stochastic or variability uncertainty. This uncertainty is usually due to measurable elements [WIN 96], and it is considered irreducible because it is only due to the natural variations of physical phenomenon [BAE 04]. Aleatory uncertainty is usually associated with objective knowledge coming from generic knowledge or singular observations.

– Epistemic uncertainty is due to the imprecise character of knowledge or associated with the lack of knowledge. It is usually associated with non-measurable quantities [WIN 96] and it is considered as reducible since new information can reduce or eliminate this type of uncertainty. It is mainly encountered with subjective data based on beliefs and can be quantitative or qualitative.

1.3. Sources of uncertainty

An important question comes from the sources of uncertainty. These sources are our own inability to know the exact values or state of the system and its components in the dependability point of view. This inability can be technical or conceptual. For instance, Pate-Cornell [COR 96] used six levels of uncertainty to obtain a family of risk curves in the presence of both aleatory and epistemic uncertainties. Smithson [SMI 89] proposed a taxonomy of ignorance (see Figure 1.1). In his work, ignorance is considered multiple and at several levels. Ignorance is the top level concept of his taxonomy. Some parts of this taxonomy concern irrelevance of knowledge but they are outside the scope of our work. The second part concerns error and is well developed but less clear for our purpose.

We can also add to this list of knowledge imperfection the notion of inconsistency which appears when knowledge is formulated by one or several sources that provide contradictory information [OSE 03].

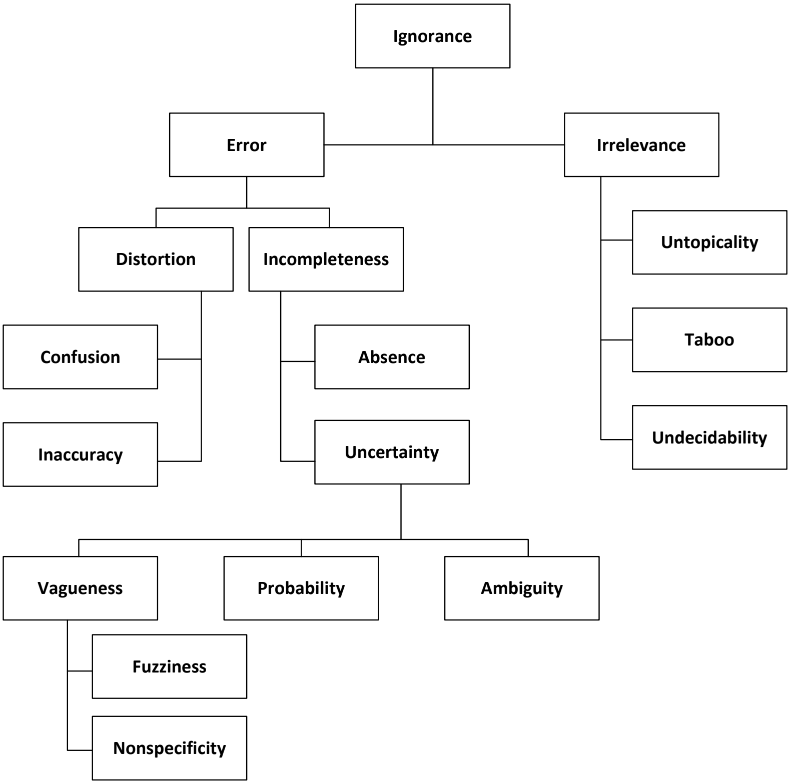

Figure 1.1. *Taxonomy of ignorance*

For our purpose of numerical assessment of risk and dependability, we prefer the taxonomy proposed by Fisher [FIS 99] which is a particular point of view of the Smithson taxonomy (see Figure 1.2). This taxonomy seems more convenient and refers to a current meaning, for instance, developed in the special issue of Reliability Engineering & System Safety [HEL 04].

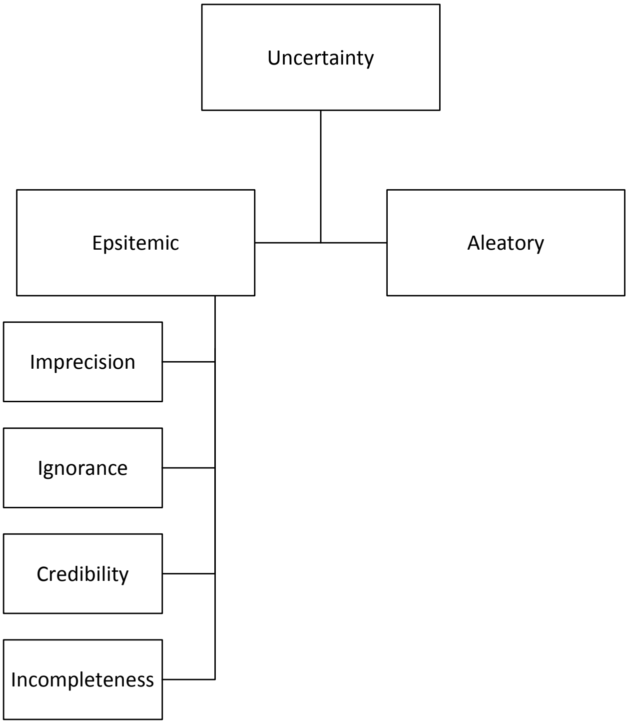

Figure 1.2. *The taxonomy of uncertainty considered*

Aleatory or random uncertainty has its roots in the natural variability of physical phenomena, as shown in Figure 1.2, four notions generate epistemic uncertainty:

– imprecision corresponds to the inability to express the true value because the absence of experimental values does not allow the definition of a probability distribution or because it is difficult to obtain the exact value of a measure. For instance, only bounds are known because it cannot be different physically.

– ignorance (partial or total) corresponds to the inability to express knowledge on disjoint hypotheses. Sometimes, it is easier to express knowledge on their disjunctions. Indeed, what is more imprecise is more certain [SME 97].

– incompleteness corresponds to the fact that not all situations are covered. For instance, all the failure modes of a material are not known.

– credibility concerns the weight that an agent can attach to its judgment. It is a sort of second-order information.

Imprecision, ignorance and incompleteness are closed notions. Incompleteness is a kind of model uncertainty, whereas ignorance and imprecision more concern parametric uncertainty. Imprecision and ignorance are different because the first is linked to the quality of the value, whereas the second is associated with the knowledge of the value.

For epistemic uncertainty, [BOU 95b] considered that knowledge imperfections can be sorted in three main types: uncertainty that represents doubt of the knowledge validity, imprecision that corresponds to a difficulty to express or to obtain the knowledge, and incompleteness that corresponds to the absence of knowledge or to partial knowledge.

In addition, uncertainty can impact both the model and its parameters [DRO 09, IPC 06]. Parametric uncertainties mainly concern the input values, whereas the model uncertainty concerns the difference between the model and the reality. Model uncertainty also integrates completeness associated with model partiality or its scale of validity. [OBE 02] defined the notion of errors which can be linked to model uncertainty. It is closed to error induced by the use of some mathematical models (probability, theory of belief function, etc.) or knowledge management tools and their uncertainty.

1.4. Conclusion

In conclusion, exact knowledge is very difficult to obtain so it implies that uncertainty is inevitable. It is clear that uncertainty can be epistemic or aleatory and can affect the model and the parameters. Dealing with uncertainty is complex and the terminology difficult to use. According to Smitshon [SMI 89] and more particularly Fisher [FIS 99], the situations that generate ignorance and imperfection are numerous and as said by Dubois [DUB 10], it depends on the situation to elicit knowledge. To model and analyze knowledge, it is necessary to use convenient mathematical languages or frameworks to produce coherent and credible results.

For this purpose, we have divided the book into several chapters. For the sake of illustration, we have applied these approaches to the assessment of the performance of a lot of typical systems, such as safety instrumented systems, and with different models (fault trees and Markov chains).

Chapter 2 concerns the mathematical modeling languages/frameworks. In Chapter 3, we show how to model uncertainties of expert judgments for the allocation of SIL with risk graphs or risk matrices by using fuzzy sets or evidence theory (also named belief functions theory). Chapter 4 is dedicated to interval valued probabilities in dependability assessment. In Chapter 5, we introduce the concept of evidential networks, which is a graphical model like Bayesian networks but considers several forms of uncertainties. Evidential networks are applied to assess some dependability parameters of systems. Temporal variations are also considered through dynamic evidential networks. Chapter 6 is dedicated to importance measures in dependability analysis using evidential networks and considering several uncertainties.

The conclusion draws together the main contributions of the chapters to managing several forms of uncertainty with several models.